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Development of Multi-Sensor Convergence Monitoring and Diagnosis Device based on Edge AI for the Modular Main Circuit Breaker of Korean High-Speed Rolling Stock

[1]Byeong Ju Yun[*], [1]Jhong Il Kim, [1]Jae Young Yoon, [2]Jeong Jin Kang, [3]You Sik Hong

[1]R&D Institute, Tae Hee Evolution Co. Ltd., Seoul, Korea*
[2]Proffessor, Dept. of Information and Communication Engineering,
Dongseoul University, Seoul, Korea
[3]Proffessor, Dept. of Information Engineering Software,
Sangji University, Wonju-Si, Kangwon-do, Korea
{ [*]bjyunster, kjhongil, njud145 }@gmail.com, jjkang@du.ac.kr,
Corresponding Author : yshong@sangji.ac.kr

Abstract

This is a research thesis on the development of a monitoring and diagnosis device that prevents the risk of an accident through monitoring and diagnosis of a modular Main Circuit Breaker (MCB) using Vacuum Interrupter (VI) for Korean high-speed rolling stock. In this paper, a comprehensive MCB monitoring and diagnosis was performed by converging vacuum level diagnosis of interrupter, operating coil monitoring of MCB and environmental temperature/humidity monitoring of modular box. In addition, to develop an algorithm that is expected to have a similar data processing before the actual field test of the MCB monitoring and diagnosis device in 2023, the cluster analysis and factor analysis were performed using the WEKA data mining technique on the big data of Korean railroad transformer, which was previously researched by Tae Hee Evolution with KORAIL.

Keywords: *Edge AI, Monitoring and Diagnosis Device, Vacuum Level Monitoring and Diagnosis, Temperature and Humidity Monitoring and Diagnosis, Operating Coil Monitoring and Diagnosis, Data Mining*

1. INTRODUCTION

This thesis is about a monitoring and diagnosis device of the vacuum interrupter used in the vacuum circuit breaker. This thesis is an experiment on monitoring means that can monitor the deterioration of a vacuum circuit breaker by detecting a degradation in vacuum level.

In general, a circuit breaker is an electrical protection device that protects a load device and a line from such a fault current in the event of an accident such as a short circuit or a ground fault that may occur in an electric circuit. Depending on the arc extinguishing medium, the circuit breaker is classified into an inflow circuit breaker using oil as an arc extinguishing medium, a gas circuit breaker using SF6 gas, an inert gas, an air circuit breaker using air as an arc extinguishing medium, a circuit breaker using magnetism, and a vacuum

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Corresponding Author: yshong@sangji.ac.kr
Tel:+82-2-970-5607, Fax: +82-2-970-5981
Professor, Dept. of Information Engineering Software, Sangji Univ., Korea

circuit breaker using a vacuum dielectric strength. The vacuum interrupter is a core part applied to vacuum circuit breakers, vacuum switches, and vacuum contactors to cut off load current or fault current in the power system.

The domestic modular main circuit breaker (MCB) system was first applied to the EMU-260 (2018), but since there is no localized product, localization development is in progress through the railway vehicle parts development project. As the main contents of differentiated development, it is possible to minimize and optimize the maintenance performed regularly through the real-time status monitoring function of the modular main circuit breaker by developing and applying a circuit breaker diagnosis and monitoring device, and to prevent accidents based on the state monitoring prior to the main circuit breaker accident. In addition, it can be used for scientific device life extension and optimal operation through the accumulation of operating state data of the main circuit breaker system and comparative analysis of trend data. The main circuit breaker is installed on the top of the electric railway vehicle and quickly cuts off overcurrent in the event of an accident such as a short circuit / ground fault in the power supply system to protect the vehicle and prevent the spread of accidents. Vacuum Interrupter is a key component that determines the lifespan of the main circuit breaker, and high vacuum must be maintained to secure insulation and breaking performance.

In addition, in order to guarantee 100,000 times of operation during the lifetime, the circuit breaker must maintain the operating characteristics according to the secular change. However, the VI's vacuum level decreases due to causes such as cracks in the insulation container or natural leakage, and when it changes beyond a certain value, the insulation performance and breaking performance are lost. This characteristics change in status is a major failure of the main circuit breaker and the consequent ripple effect of the accident. Therefore, it is necessary to constantly monitor and diagnose the vacuum level of the main circuit breaker and the operation characteristics of the operating coil in order to prevent such failures and their spread. In addition, it is necessary to collect environmental monitoring data in the module box on top of the vehicle, analyze the correlation with major monitoring and diagnosis data, and use it to improve the operational performance of the modular main circuit breaker in the future.

In this study, a multi-signal sensor module that analyzes the change in vacuum level by sensing the partial discharge (PD) signal generated inside the VI, analyzes the operation characteristics of the operating coil, and changes in environmental temperature and humidity. A diagnostic module that comprehensively analyzes and diagnoses data from sensor module, was implemented by using machine learning to improve the performance of the monitoring and diagnosis function.

The structure of this thesis is as follows. In Chapter 2, the discharge phenomenon that occurs inside the insulation material of high voltage (HV) devices due to the presence of voids, impurities or cracks due to defects in the manufacturing process, mechanical stress or insulation aging process is discussed.

Chapter 3 describes the transformer fire accident factor analysis system using artificial intelligence techniques, and Chapter 4 explains the results of cluster analysis and factor analysis using WEKA data mining techniques and TENSOR FLOW open source to prevent transformer fires.

2. PARTIAL DISCHARGE IN HV EQUIPMENT

Partial Discharge (PD) is a discharge phenomenon that occurs inside the insulating material of high voltage (HV) devices due to the presence of voids, impurities or cracks due to defects in the manufacturing process, mechanical stress or insulation aging process. PDs that only partially bridge the insulation between conductors occur repeatedly in a small area and are therefore called partial discharges. In other words, partial discharges appear as pulses with a duration of approximately a few nanoseconds, leading to a frequency range above 1 GHz. PD destroys the local insulation structure, resulting in insulation deterioration, and eventually spreads through the entire insulation in the long term, causing failure of the HV device. Failure of HV equipment has sudden and catastrophic consequences, resulting in economic loss and safety loss.

As the applied voltage rises, the size and number of discharge pulses gradually increase, reaching the maximum value and then disappearing. The sensor module implemented in this paper is installed in the module box on the top of the vehicle as shown in Figure 1, and has multi-sensing functions like as monitoring of vacuum level based on PD sensing, monitoring of circuit breaker operation characteristics based on MCB status and coil current sensing, and monitoring of environment temperature and humidity in module box. It has multi-sensor data acquisition function and Ethernet-based high-speed mass sensor data linkage function.

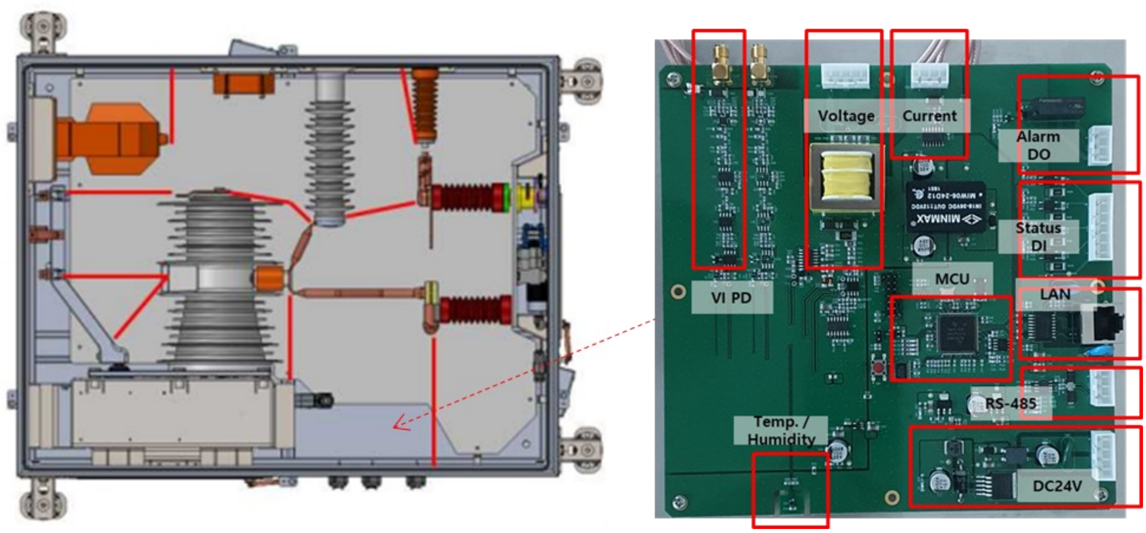

Figure 1. Installation and Configuration of the Sensor Module

As shown in Figure 2, the diagnosis module is installed inside the vehicle switchboard, collects, analyzes, and diagnoses data from the sensor module, and is implemented to have various external communication linkage functions.

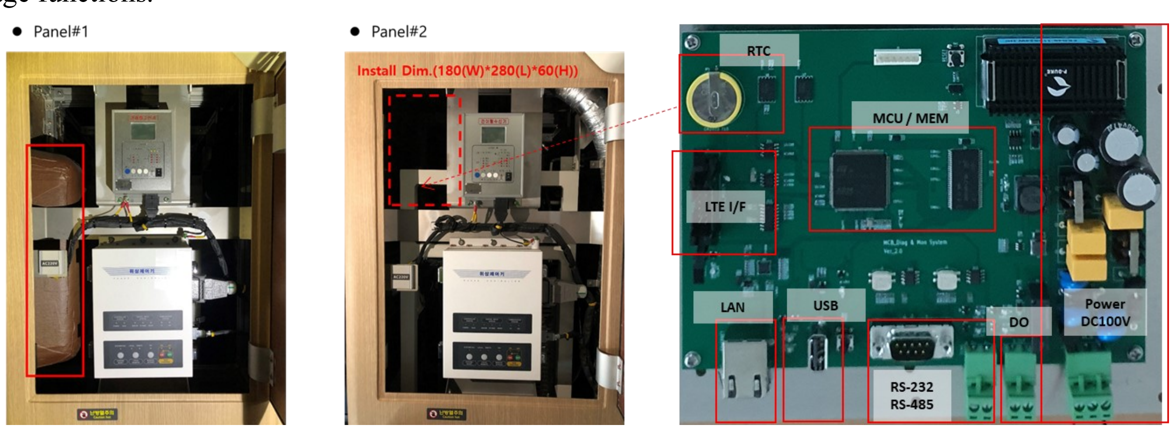

Figure 2. Installation and Configuration of the Diagnosis Module

The PD signal for vacuum level monitoring and diagnosis, which is a large amount of high-speed sensor data among multiple sensor data, was sampled with 256 sampling data per cycle (60Hz, 16.7msec). The processing of sampling data was processed and analyzed as shown in Figure 3.

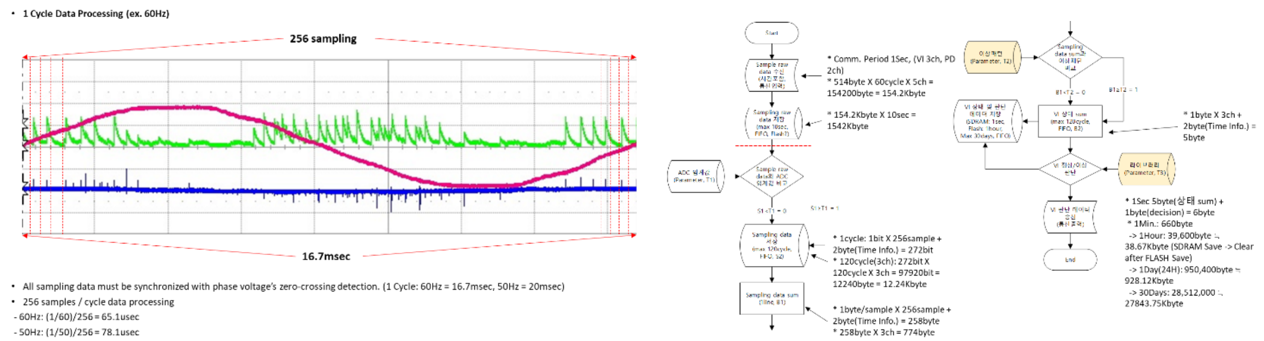

Figure 3. Data Processing for the Vacuum Level Diagnosis

The monitoring and diagnosis program of the diagnosis module is composed of a sensor module-linked monitoring and diagnosis process and various externally linked processes, and was produced as shown in Figure 4.

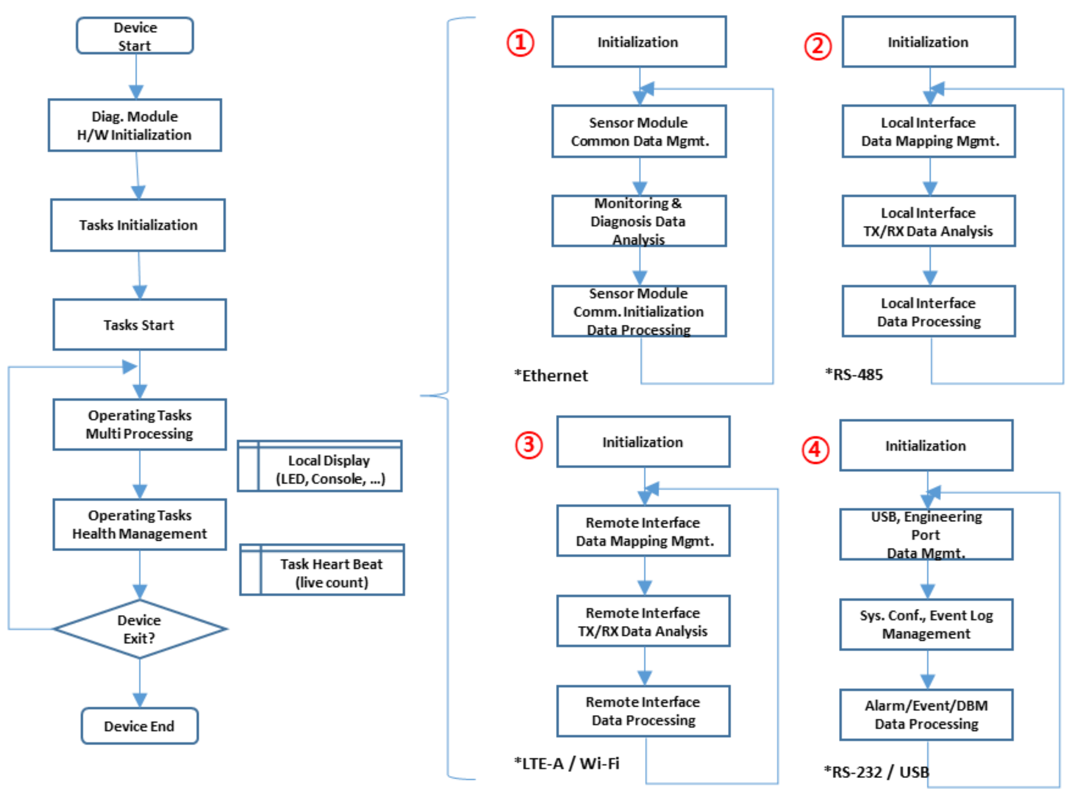

Figure 4. Monitoring and Diagnosis Program Configuration in Diagnosis Module

3. DATA MINING BASED ON SIMULATON

In this paper, in order to develop an algorithm that is expected to have a similar data processing before the actual field test of the MCB monitoring and diagnosis device in 2023, the cluster analysis and factor analysis were performed using the WEKA data mining technique on the big data of 33,866 data from 04:00 on July 22, 2018 to 16:27 on August 14, 2018 for Korean railroad transformer, which was previously researched and collected by Tae Hee Evolution with KORAIL. Table 1 describes the actual data of transformer fire risk. Independent variables are humidity condition, temperature condition, load current value, oil level, oil temperature, winding temperature, and six variables, and one dependent variable is fire accident judgment risk. Figure 5 explains the results of cluster analysis of 33,866 pieces of transformer accident risk analysis data.

Table 1. Power Equipment (Transformer) Accident Risk Analysis Data (7 Variables)

Variables	Analysis (Monitoring and Diagnosis) Item	Analysis Result (State)
Variable1	**Environment Humidity Condition**	Low, Medium, High
Variable2	**Environment Temperature Condition**	Low, Medium, High
Variable3	**Load Current Condition**	Low, Medium, High
Variable4	**Oil Level Condition**	Low, Medium, High
Variable5	**Oil Temperature Condition**	Low, Medium, High
Variable6	**Winding Temperature Condition**	Low, Medium, High
Variable7	**Fire Accident Risk**	Yes, No

Viewer

Relation: TRAIN

No.	1: Instance_number Numeric	2: ATR3.AIR_HUMI Numeric	3: ATR3.AIR_TEMP Numeric	4: ATR3.LOAD_CURRENT Numeric	5: ATR3.OIL_LEVEL Numeric	6: ATR3.OIL_TEMP Numeric	7: ATR3.WINDING_TEMP Numeric	8: Cluster Nominal
30790	30789.0	50.2	34.7	2.8125	0.03125	52.375	53.125	cluster1
30791	30790.0	50.2	34.7	2.8125	0.03125	52.375	53.125	cluster1
30792	30791.0	50.1	34.7	2.5	0.03125	52.875	53.25	cluster1
30793	30792.0	49.9	34.7	3.4375	0.03125	52.75	53.25	cluster0
30794	30793.0	49.8	34.7	9.0625	0.03125	53.0	53.25	cluster0
30795	30794.0	49.9	34.7	2.1875	0.03125	52.375	53.25	cluster1
30796	30795.0	49.7	34.8	3.125	0.03125	53.0	53.25	cluster0
30797	30796.0	49.6	34.8	2.5	0.03125	52.5	53.375	cluster1
30798	30797.0	49.6	34.8	2.5	0.03125	53.0	53.25	cluster1
30799	30798.0	49.5	34.9	2.8125	0.03125	53.0	53.25	cluster1
30800	30799.0	49.5	34.8	2.8125	0.03125	52.625	53.25	cluster1
30801	30800.0	49.6	34.8	2.5	0.03125	53.0	53.25	cluster1
30802	30801.0	49.7	34.8	2.8125	0.03125	52.5	53.375	cluster1
30803	30802.0	49.8	34.8	2.8125	0.03125	53.0	53.375	cluster1
30804	30803.0	49.8	34.8	2.8125	0.03125	52.5	53.375	cluster1
30805	30804.0	49.9	34.8	2.8125	0.03125	53.0	53.25	cluster1
30806	30805.0	49.9	34.9	2.8125	0.03125	52.875	53.375	cluster1
30807	30806.0	49.4	34.9	4.375	0.03125	53.125	53.375	cluster0
30808	30807.0	49.2	34.9	10.9375	0.03125	53.0	53.375	cluster0
30809	30808.0	49.1	35.0	3.75	0.03125	52.5	53.375	cluster0
30810	30809.0	49.1	34.9	2.5	0.03125	53.125	53.375	cluster1
30811	30810.0	49.2	34.9	2.5	0.03125	53.125	53.375	cluster1
30812	30811.0	49.4	34.9	5.625	0.03125	53.375	53.375	cluster0
30813	30812.0	49.4	34.9	2.8125	0.03125	53.125	53.5	cluster1
30814	30813.0	49.4	34.9	3.125	0.03125	52.875	53.5	cluster0
30815	30814.0	49.5	34.9	2.8125	0.03125	53.0	53.5	cluster1
30816	30815.0	49.6	34.9	2.8125	0.03125	53.375	53.375	cluster1
30817	30816.0	49.7	35.0	5.3125	0.03125	53.375	53.5	cluster0

Figure 5. Accident Risk Analysis Data for the Power Equipment (Transformer) Monitoring

As shown in Figure 6, when the winding temperature exceeds 50.375 degrees, the transformer is classified as a hazardous condition.

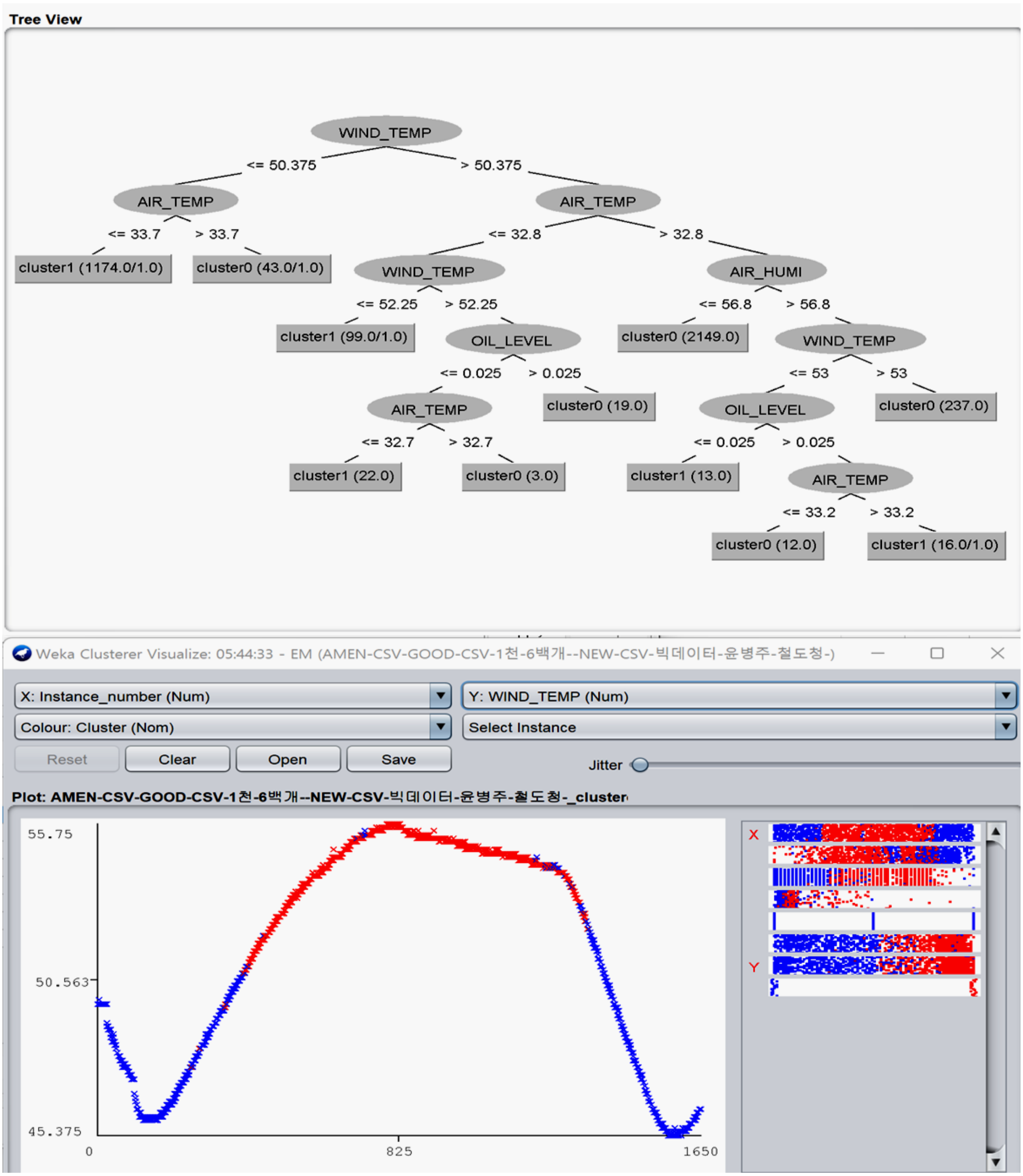

Figure 6. Result of Cluster Analysis and Factor Analysis (Device Accident Risk)

If the winding temperature is less than 50.375 degrees, it explains that the transformer is classified as steady state. If the oil level exceeds 0.025, the transformer is classified as dangerous, and if the oil level is less than 0.025, the transformer is classified as normal.

In addition, it explains that if the current value exceeds 34.0625, the transformer is classified as a dangerous state, and if the current value is less than 34.0625, it is classified as a normal state.

4. CONCLUSION

In this paper, a monitoring and diagnosis device was implemented using multiple sensors for monitoring and diagnosing the VI vacuum level, breaker operating characteristics, and environmental temperature and humidity of the main circuit breaker system for railway vehicles, and the comprehensive monitoring and diagnosis function for predictive maintenance of the integrity of the breaker system was tested. In addition, in this paper, in order to prevent transformer fires, cluster analysis and factor analysis were performed using the WEKA data mining technique on the available big data of the railway station's transformers, which were previously researched by Tae Hee Evolution.

In addition, in order to prevent transformer blackout accidents and to improve the MCB diagnosis module algorithm, as a future plan, data characteristics analysis by unsupervised learning was performed based on self-test data of each monitoring and diagnosis function. In the future, we plan to conduct demonstration experiments by selecting and implementing the optimal lightweight edge AI algorithm to realize operation and maintenance optimization through predictive maintenance of the main circuit breaker system.

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